Estimation of Arm Movement from the Neural Activities of the Primary Motor Cortex

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Abstract: We succeeded in reconstructing muscle activities from neural activities and in reconstructing joint angles during static condition. However, the reconstructed joint angles during movement did not have a good correlation with the real joint angles. Therefore, we adopted a servo mechanism to compensate for the error in the joint angles. This error mainly arises due to muscle properties such as the velocity-tension relationship or the length-tension relationship. In order to overcome the limitations due to these muscle properties, we divided an artificial neural network into two networks—one for movement control and one for posture control. We also trained the gating network to switch between the two neural networks. As a result, the gating network switched the modules properly, and the accuracy of the estimated angles improved.

Key Words: BMI, EMG, Neural activity, M1, arm movement

1 Introduction

Interest in the field of brain machine interfaces has been increasing in recent years and many papers have been published [7], [8], [9], [10]. A brain machine interface is a technology for paralyzed people who cannot move their arms due to damage from an accident or a disease. The main goal is to allow paralyzed people to interact with society more freely by giving them control over an external device, such as a robot arm or a mouse cursor, from brain signals through a mathematical model.

Since 1999, when Chapin et al. [3] controlled the arm movement of a robot in one degree of freedom from the neural activity of the motor cortex of a rat, considerable research and development has been done in this field. Carmena et al. [4] succeeded in reconstructing the arm movement of a robot in three degrees of freedom and grip force from the neural activity of the premotor cortex, the primary motor cortex, and the posterior parietal cortical area of a monkey. In addition, Musallam et al. [5] extracted high-level signals, such as the goal of a movement and the preference and motivation of a subject, from the neuron signals of the parietal reach region (PRR) and area 5, which are the major pathways of visually guided movement. Recently, Hochberg et al. [6] succeeded in controlling a computer cursor on a two-dimensional display from the signal of the primary motor cortex of the brain of a human.

In order to implement a brain machine interface system similar to a human arm, it is essential to reconstruct the position and force information of the arm from the neural activity of the brain. For example, let us consider the case of a human picking up an object; the human first moves his arm to the position of the object from the original position of the arm and then grips the object with a proper force depending on the weight of the object. Therefore, the reconstruction of the force information is an important factor in the implementation of a brain machine interface system. We used electromyography (EMG) signals to simultaneously reconstruct the position and force information. Since EMG signals reflect muscle tensions, we can precisely reconstruct the arm posture, joint torque, and stiffness from the EMG signals.

Until now, several hypotheses have been proposed to describe the relationship between the neural activities of the primary motor cortex and motor control. Among these hypotheses, one states that the neural activities of the primary motor cortex encode movement direction [24], another states that the neural activities encode force [1], and yet another states that the neural activities encode both the movement direction and force [2]. Despite these endeavors, the exact relationship between the neuron activities in the primary motor cortex (M1) and motor control remains
unknown.

Previous studies to determine the relationship between the neural activities of the primary motor cortex and motor control analyzed the correlation between the neural activities of M1 and the magnitude and direction of movement or force. However, the actuator that generates movement and force is a muscle. We have proposed computational models [11],[17],[18],[21] to estimate joint torque, joint angle, impedance, and so on from the activity of muscles. By using these models, we can estimate movement direction and force from the activity of muscles. Some studies have used these results to devise a model to determine the relationship between the neural activities of the primary motor cortex and movement; this relationship cannot be determined by the conventional method of calculating the correlation between the neural activities and movement. For example, Todorov [27] has proposed a model that generates movement. In this model, since the activity of muscles is made by inserting a time-delay term into the neural activities of the primary motor cortex, muscle activity simply becomes a linearization of neural activities. The force generated in the muscles was estimated by using a first-order model from two parameters-the length of muscles and the contract velocity.

We considered the model of the muscle as a second-order low-pass filter and therefore designed the model to have characteristics of smoothness and time delay. The low-pass filter was designed from the relationship between human muscles and force [12]. We implemented the nonlinear characteristic of muscles related to the joint angle and the contract velocity of muscles by using two different artificial neural network models. In this way, by inserting the smoothness and nonlinearity of a musculoskeletal system into the model, we can precisely reconstruct the actual movement, even when using a linear model between the neural activities of the primary motor cortex and muscle activities.

In this study, we first reconstructed nine muscle tensions (filtered EMG signals) from the neural activity of 105 neurons in M1 by using a linear regression method. We then estimated joint angles in four degrees of freedom related to the shoulder and the elbow from the reconstructed muscle tensions by using a modular artificial neural network model.

2 Materials and Methods

2.1 Behavioral Task

We trained a Japanese monkey (Macaca fuscata; male, 7.4kg) to perform a continuous arm-reaching task. The task, as shown in Fig. 1, consisted of pushing buttons in the following sequences: Hold-C-A-B, Hold-C-D-B, Hold-D-B-A, or Hold-D-C-A. These sequences are explained in greater detail below.

Here we will explain only the Hold-C-A-B sequence (See Fig. 2), as the others have similar patterns. First, the monkey pushes the hold button for 1 s when the hold signal turns on. If the monkey succeeds in pushing the hold button for 1 s, the C button turns on and the monkey has to push the C button within 1 s. After pushing the C button, the A button turns on. As in the case of the C button, if the monkey pushes the A button for 1 s, the B button turns on, and the monkey should push the B button for 1 s. The monkey received juice rewards if the task was completed successfully. All procedures were approved by the Tohoku University Animal Care and Use Committee.

Figure 1: Behavioral task: The monkey, trained to perform a continuous arm-reaching task, sat in a primate chair with its head fixed and facing a touch panel equipped with five lamps and five buttons.

Figure 2: A sequential arm-reaching task (Hold-C-A-B sequence).
2.2 Recording Neural Activity In the Primary Motor Cortex

After the monkey became sufficiently skilled at the task, a stainless steel recording chamber (diameter 20 mm) was installed around the primary motor cortex of the left hemisphere under aseptic conditions. By using a glass-insulated Elgiloy alloy microelectrode, the neural activity of the upper part of the body in the primary motor cortex was measured by the conventional chronic single-unit recording method. The main recording target was the neurons located in layer V. For controlling the microelectrode, an electronic stepping microdrive (MO-81, Narishige) was used. The neural activity was measured at a sampling rate of 1 kHz. In order to determine which muscle is linked to which neuron measured in the primary motor cortex, we used intracortical microstimulation (ICMS). We identified the muscle that moves or contracts when a train of 12 cathodal pulses of 0.2 ms duration at 300 Hz was applied at each neuron at an intensity below 40uA.

In all, 161 neurons were measured in the primary motor cortex (Fig. 3). Among these neurons, 66 were related to the shoulder muscle, and 39 were related to the elbow muscle. The rest were the neurons related to the wrist and finger. To reconstruct arm posture, we used 105 neurons related to the shoulder and elbow muscles in 31 places.

In Fig. 4, each row represents each trial and each dot shows the firing of the neuron. The three marks in each trial represent the appearance of the task events, as denoted in the figure. Spike density functions (SDFs) are drawn (bin width = 30ms) below each raster display. Both raster and spike density functions are aligned to the movement onset time.

In Fig. 5, signal processing of the neural activity. The dots drawn near the top of the figure represent the firing of the neuron at each trial. These signals become the purple lines at the lower part of the figure by adding per 1 ms unit, and then the signals were summed within non-overlapping 30 ms time bins, shown in the blue blocks.
As shown in Fig. 5, the neural activities measured at a sampling rate of 1 kHz were summed within non-overlapping 30 ms time bins. On average, neural activities were measured 10.88 trials at each neuron, and we used half of the data as training data and the remainder as the test data.

2.3 EMG Signal Processing

EMG signals were measured in nine muscles related to four degrees of freedom (Fig. 6). In order to measure the EMG signals, we used a silver/silver chloride surface electrode (NE-102, Nihon Kohden). After differential amplification, each signal was sampled at 1 kHz with a 12-bit resolution. The signals were digitally rectified, averaged over 5 ms, and then filtered through a second-order low-pass filter with a cut-off frequency of approximately 3 Hz [12].

\[
f_{EMG}(t) = \sum_{j=1}^{n} h_j EMG(t - j + 1)
\]

\[
h(t) = 6.44 \times (e^{10.80t} - e^{16.52t})
\]

The coefficients \(h_j\) in equation 1 can be acquired by sampling \(h(t)\) in equation 2 discretely. The resulting signal is very similar to the actual tension; hence, it is called quasi-tension [13].

The method that uses a low pass filter to estimate muscle tension shows good performance when the velocity of muscle contraction is slow. However, the method cannot estimate muscle tension precisely when the velocity of contraction is very high, and the method does not consider the nonlinear characteristic of muscle, such as the length and the velocity. However, it is feasible that the output of the low pass filter is similar to the actual tension [15].

2.4 Kinematics

In order to measure the position of the shoulder, the elbow, and the wrist of the monkey, we attached an infrared marker on the arm of the monkey and measured each position by using a 3D position measurement system (MacReflex, Qualisys). The sampling rate was 120 Hz. In order to calculate the joint angles of the four degrees of freedom in the shoulder and elbow from the positions measured, we used the inverse kinematics equations [11].

3 Results

3.1 Estimation Result of Filtered EMG Signals from Neural Activity of Primary Motor Cortex

The estimation of the filtered EMG signals was obtained by linearizing the neural activities of the primary motor cortex by using a linear regression method.

\[
f_{EMG_i}(t + \delta t) = \sum_{j=1}^{m} \omega_{ij} n_j(t) + bias
\]

Here, \(f_{EMG_i}\) and \(n_j\) describe the \(i\)th filtered EMG signal from the \(j\)th neuron. \(\delta t\) is the delay between the neuron activity of the primary motor cortex and the EMG signals. The weighting factor \(\omega_{ij}\) represents the strength influence from neuron \(j\) on muscle \(i\).

We estimated the filtered EMG signals from 105 neurons in the primary motor cortex by using equation 3. To decide the delay-time parameter, we used the ICMS method where we electrically stimulated nine locations of the primary motor cortex 275 times, and noted the time at which the EMG signals occurred. The delay time was 16.57 ± 3.46 ms; we therefore used a delay of 17 ms when we estimated the filtered EMG signals from the neural activities of the primary motor cortex.

Fig. 7 represents the results of the estimation of the neural activities to the filtered EMG signals. The estimated filtered EMG signals had a correlation coefficient of 0.93 with the actual EMG signals.

3.2 Estimation of Joint Angles from the Filtered EMG Signals

In order to estimate joint angles from the filtered EMG signals, we used a modular artificial neural network [14], as shown in Fig. 8. Training the data pertaining
Reconstruction of the filtered EMG signals by using the ensemble of 105 neurons of the primary motor cortex. The dotted lines (blue) represent the actual filtered EMG signals, and the solid lines (red) show the reconstructed filtered EMG signals.

to posture and movement in different networks will improve the accuracy of the estimation of joint angles as compared to training the entire data in the same network, since the muscle tension is different in the two mentioned cases. If training is done well, a gating network will select one of the two expert networks by its input signal. In this case, one of the two expert networks is used for posture control, and the other is used for movement control. Since the gating network decides the output ratio for each expert network depending on its input signal, the sum of the outputs of the gating network should always be equal to 1.

To achieve this, as shown in equation 4, the output \( g_j \) of the gating network, which corresponds to the jth expert network is normalized by using the soft max activation function.

\[
g_j = \frac{e^{x_j}}{\sum_{i=1}^{N} e^{x_i}} \quad (4)
\]

Here, \( x_i \) is the value determined by the input signal of the gating network and \( N \) is the total number of outputs of the gating network. The total output is calculated by multiplying the output of the gating network by the output of each expert network and summing the result, as given in equation 5.

\[
\theta = \sum_{i=1}^{N} g_i \hat{\theta}_i \quad (5)
\]

The gating network and each expert network are trained to maximize the likelihood function \( \ln L \) (equation 6) by the back propagation algorithm [16].

\[
\ln L = \ln \left( \sum_{i=1}^{N} g_i e^{-\frac{||\theta - \hat{\theta}_i||^2}{2\sigma_i^2}} \right) \quad (6)
\]

The update of the weights of the gating network is calculated by the chain rule, as in equation 7.

\[
\frac{\partial \ln L}{\partial x_i} = \sum_{i=1}^{N} (g(i|X, \hat{\theta}_i) - g_i) \quad (7)
\]

Here, \( X \) is the input of the gating network and the posteriori probability \( g(i|X, \hat{\theta}_i) \) is

\[
g(i|X, \hat{\theta}_i) = \frac{g(i) e^{-\frac{||\theta - \hat{\theta}_i||^2}{2\sigma_i^2}}}{\sum_{j=1}^{N} g_j e^{-\frac{||\theta - \hat{\theta}_j||^2}{2\sigma_j^2}}} \quad (8)
\]

The update of the weights of each expert network is calculated by chain rule as in equation 9.

\[
\frac{\partial \ln L}{\partial \theta_i} = \sum_{i=1}^{N} g(i|X, \hat{\theta}_i) \frac{\theta - \hat{\theta}_i}{\sigma_i^2} \quad (9)
\]

Each network is trained by using the kick-out method.
Figure 9: The output of the gating network for the different sequences. The solid line represents the moment of posture and the dotted line shows the moment of movement.

The filtered EMG signals of the nine muscles were used as the input of each expert network model. The summed-squared velocity value of the four joint angles was used as the input of the gating network. When the value of the neural activities in M1 was directly used as the input of the gating network, the gating network could not distinguish between posture and movement. However, when using the summed-squared velocity value of the four joint angles as the input, the gating network distinguished posture and movement correctly. After measuring 30 trials of the EMG signals and movement trajectories of the arm of the monkey, we used 29 trials as training data and one trial as the test data. The number of training data samples was 522348 (29 trials × 1 kHz × 4.503 sec × 4 cases) and the number of test data samples was 18012 (1 trial × 1 kHz × 4.503 sec × 4 cases). In the case of the gating network, the network was trained by the summed-squared velocity value of the four joint angles. However, since the summed-squared velocity value of the four joint angles cannot be used as test data, we estimated the velocity values from the filtered EMG signals. Fig. 9 shows the outputs of the gating network when the estimated squared acceleration values of the four joint angles were inputted and Fig. 10 represents the estimated four joint angles from the neural activity of the primary motor cortex. The correlation coefficient between the estimated joint angles and the actual joint angles was about 0.92.

4 Discussion

We reconstructed muscle tensions from the neural activity of the primary motor cortex related to the shoulder and the elbow. Then, we estimated the joint angles from the reconstructed muscle tensions. When reconstructing the muscle tensions from the neural activity, we could determine the delay time by examining the correlation coefficient between neural activity and EMG signals. However, the EMG signal is a simple waveform that has one or two peaks, and the neural activity is similar. Therefore, determining the delay time by using the correlation coefficient is very difficult. In this study, after determining the delay time by using ICMS, we fixed the δt when reconstructing the muscle tensions from the neural activity of M1.

The reason why we do not directly estimate arm posture from the neural activity of the primary motor cortex, and instead use the muscle tensions, is that since muscles are anatomically linked to M1 by two or three neurons through the spinal cord, we can get a signal that is highly correlated with M1. When a human assumes a posture, the brain stabilizes the posture by controlling the muscle tensions. Therefore, by using muscle tensions, we can reconstruct arm posture more precisely than by using the existing method that directly reconstructs arm posture from the neural activity of M1. If EMG signals are reconstructed from the neural activity of M1, there is a possibility that a paralyzed person can control his arm by using the estimated EMG signals as command signals for a functional electrical stimulation (FES) system [19],[20].

We used the modular artificial neural network
model when reconstructing joint angles from muscle tensions. The reason is that in the case of isotonic movement, where force is outputted with a changing length of the muscle, the tension is different depending on the velocity that the muscle flexes or extends. In the case of a muscle flexion, the tension will decrease as the flex velocity increases. In the case of muscle extension, the tension will increase as the extension velocity increases. We could improve the estimation performance of joint angles by training two networks with tension values, which changes depending on the velocity, rather than training the data in the same network. We used one network for 0 velocity and the other for movement velocity.

Miller et al. [26], without modeling the characteristics of the musculoskeletal system, controlled arm movement by electrical stimulation of arm muscles through FES after reconstructing EMG signals from the neural activities in M1. However, if we model the musculoskeletal system, we could extend the application of the brain machine interface to such areas as robot control.

When we used neuron activities for the input of the gating network to switch the expert, it was difficult to select the proper expert. It was also difficult to switch the expert by using estimated EMG signals. This is because the neuron activities and estimated EMG signals vary during posture control by controlling the co-contraction level. The activation level of neuron activities or EMG signals did not correlate with the joint state. Therefore, we estimated each joint velocities from the estimated EMG signals and used the velocities as input signals of the gating network.

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